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Research Article

Block based Normalized LMS Adaptive Filtering Technique for Denoising EEG Artefacts

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Abstract

The electroencephalogram (EEG) is an important bioelectric signal for studying human brain characteristics as well as detection of abnormalities like epilepsy. However, the EEG recorded often contains strong artefacts produced by many sources like Powerline Interference (PLI) and Electrocardiogram (ECG). Existing regression–based methods for removing artefacts require various procedures for pre-processing and calibration that are inconvenient and time consuming. This paper introduces Block based Normalized LMS (BBNLMS) Adaptive algorithm and its sign variant algorithms for removing the PLI and ECG artefacts from the contaminated EEG signal. The simulation results show that the performance of the BBNLMS algorithm is superior to that of conventional LMS algorithm in terms of Signal to noise ratio.

Keywords: *Adaptive filters, Block based Normalized LMS, PLI, ECG, Signal to noise Ratio.*

1. Introduction

The statistical analysis of electrical recordings of the brain activity by an Electroencephalogram is a major problem in Neuroscience. Cerebral signals have several origins that lead to the complexity of their identification. Therefore, the noise removal is of the prime necessity to make easier data interpretation and representation and to recover the signal that matches perfectly a brain functioning. Common artefacts present in EEG are PLI, Eye Blink noise, ECG artefacts, muscle and respiration artefacts. (C. Fortgen et al, 1983) presented a method that automatically eliminates ECG artefacts from EEG records and creates an extracranial reference electrode in one single process. (Stephanie Devuyst et al, 2008) introduced a new automatic method to eliminate electrocardiogram (ECG) noise in an electroencephalogram (EEG). They modified the independent component analysis (ICA) algorithm by using only a single-channel electroencephalogram. To check the effectiveness of the approach, they compared it with other methods, that is, ensemble average subtraction (EAS) and adaptive filtering (AF). (Xavier Navarro et al, 2012) proposed a combination of empirical mode decomposition (EMD) and adaptive filtering (AF) to cancel electrocardiogram (ECG) noise in a simplified EEG montage for preterm infants. They introduced Empirical mode decomposition prior to Adaptive filtering which allowed them to selectively remove ECG. Apart from these EEG denoising techniques many approaches have been reported in the literature to address EEG enhancement using adaptive signal processing techniques. (S.C.Douglas, 1994) presented many data normalized LMS algorithms for noise reduction which can be specially utilized for biomedical applications. (Ching-An Lai, 2002) proposed NLMS algorithm with decreasing step size, which converge to the global minimum. (S.Olmas, 2002) considered the block LMS (BLMS) algorithm for estimating the coefficients of the linear expansion. Here, the coefficient vector is updated only once every occurrence based on a block gradient estimation. (D-H Shin et al, 2005) proposed Block based noise estimation using Adaptive Gaussian filtering. (M J. Narasimha, 2007) presented Block adaptive filter with Time-Domain update using three transforms.

Thus far, to the best of the author's knowledge, Block based Normalized LMS (BBNLMS) algorithm is not used in the contest of EEG signal noise cancellation. Data Normalisation makes the step size (μ) variable, giving fast convergence and good filtering capability. But in the clinical environment the EEG signal to be processed contains a large number of samples, then sample-by-sample filtering cause's large computational complexity. In such situations block processing is a better choice. Here the input signal is processed sample by sample, and the normalization is done block wise. We normalize the algorithm with respect to the maximum value of data values in that particular

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iteration. The algorithms thus created are the block-based Normalized LMS (BBNLMS). Also various sign based BBNLMS adaptive filter structures are presented for fast convergence rate, good filtering capability (high SNR) and low computational complexity. These are Block based Normalized Sign Regressor LMS (BBNSRLMS), Block based Normalized Sign LMS (BBNSLMS) and Block based Normalized Sign Sign LMS (BBNSSLMS) algorithms. Finally to study the performance of the filter we carried out simulations on CHB-MIT database. The structure of the paper is as follows. In Section II, the fundamentals of basic LMS algorithms and development of proposed algorithms are discussed. In Section III we have discussed about the Simulation results using Mat Lab for PLI and ECG noise removal using LMS, BBNLMS, BBNSRLMS, BBNSLMS and BBNSSLMS algorithms. Finally conclusions are presented in Section IV.

2. Proposed Implementation

2.1 Basic Least Mean Square (LMS) Algorithm

The structure of an adaptive noise canceller is shown in Fig. 1. Let the transmitted EEG signal be 's_1' transmitted over a channel to a sensor that also receives a noise n_1 uncorrelated with the signal. The combined signal and noise s_1+n_1 form the primary input to the canceller. A second sensor receives a noise n_2 uncorrelated with the signal but correlated in some unknown way with the noise n_1. This sensor provides the reference input to the canceller. Let the input to the filter n_2 be assigned as x(n). Consider the length of the adaptive filter as L. For the input vector x(n), the system generates output signal y(n) as shown in the following equation.

$$y(n) = x(n)^{T}\, w(n) = w(n)^{T}\, x(n) \quad (1)$$

The tap inputs x(n), x(n − 1), x(n − 2), ... x(n − L + 1) forms the elements of the L-by-1 tap input vector x(n), where L-1 are the number of delay elements. Correspondingly, the tap weights w(n) = $[w_0, w_1, \dots, w_{L-1}]^T$ form the elements of the L-by-1 tap-weight vector w(n).

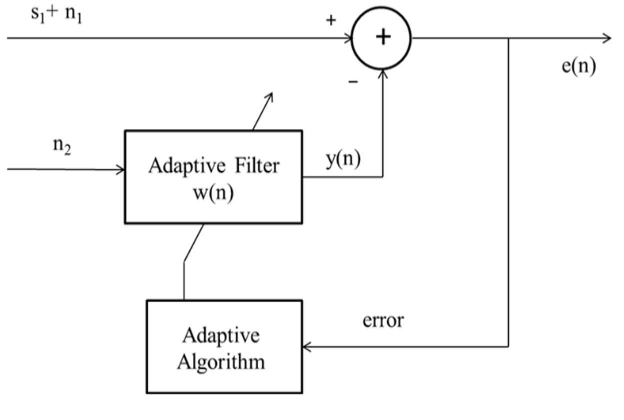

Fig.1 Adaptive Filter structure

The weight updated vector for the LMS algorithm is given by the following equation

$$w(n+1) = w(n) + \mu\, x(n)\, e(n) \quad (2)$$

Where μ is the step size and for the stationary process the LMS algorithm converges in the mean if $0 < \mu < \frac{2}{\lambda_{max}}$ and converges in the mean square if $0 < \mu < \frac{2}{tr(R_x)}$, however, since the R_x is generally unknown then either, λ_{max} or R_x, must be estimated in order to use these bounds.

2.2 Normalized LMS (NLMS) Algorithm

The weight update equation of NLMS algorithm is as follows

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{\varepsilon + ||\boldsymbol{x}(n)||2} e(n)\boldsymbol{x}(n) \quad (3)$$

For NLMS the step size is;

$$\mu(n) = \frac{\mu}{\varepsilon + ||\boldsymbol{x}(n)||2} \quad (4)$$

Where $\mu(n)$ is a Normalized step size with $0 < \mu < 2$. Replacing μ in the LMS weight update vector equation (2) with $\mu(n)$ leads to the NLMS.

Normalized Sign Regressor LMS Algorithm (NSRLMS): The weight update equation of NSRLMS is obtained from the NLMS recursion by replacing the tap-input vector x(n) with the vector sgn{x(n)}.

$$w(n+1) = \boldsymbol{w}(n) + \mu(n) sgn\{\boldsymbol{x}(n)\} e(n) \quad (5)$$

Normalized Sign LMS Algorithm (NSLMS): This algorithm is obtained from NLMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$w(n+1) = w(n) + \mu(n)\, x(n)\, sgn\{e(n)\} \quad (6)$$

Normalized Sign – Sign LMS Algorithm (NSSLMS): This can be obtained by combining normalized signed-regressor and normalized sign recursions, resulting in the following recursion:

$$w(n+1) = w(n) + \mu(n)\, sgn\{x(n)\}\, sgn\{e(n)\} \quad (7)$$

2.3 Proposed Block based Normalized LMS Algorithm

The Least Mean Square (LMS) algorithm is familiar and simple to use for cancellation of noises. However, the low convergence rate and low signal to noise ratio are the limitations for this LMS algorithm. To reduce the computational complexity we adopt block processing of normalized algorithms here we are considering overlapping blocks. In the block based approach input data is partitioned into blocks and the maximum magnitude within each block is used to compute variable step size parameter.

With this, the weight update relations for NLMS as given by (3) and its sign based versions NSRLMS, NSLMS and NSSLMS given by (5) (6) (7) takes the following form. Now the weight update relation of Block Based NLMS (BBNLMS) algorithm for $x_{Li} \neq 0$ and $\varepsilon = 0$ is written as,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{x_{Li}^2}\boldsymbol{x}(n)e(n) \quad (8)$$

Similarly the weight update relations for Block Based NSRLMS (BBNSRLMS), Block Based NSLMS (BBNSLMS) and Block Based NSSLMS (BBNSSLMS) algorithms are written as follows,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{x_{Li}^2} Sign\{\boldsymbol{x}(n)\}\, e(n); \quad (9)$$

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{x_{Li}^2}\boldsymbol{x}(n) Sign\{e(n)\}; \quad (10)$$

and

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{x_{Li}^2} Sign\{\boldsymbol{x}(n)\} Sign\{e(n)\} \quad (11)$$

Where, $x_{Li} = \max\{|x_k|, k \in Z_i'\}, Z_i' = \{iL,\ iL+1, \dots, iL+L-1\}, i \in Z$, and for $x_{Li} = 0$ and $\varepsilon = 0$ the equations (8)-(11) becomes $\mathbf{w}(n+1) = \mathbf{w}(n)$.

2.4 Computational Complexity Issues

As the sign based algorithms are largely free from the MAC operations, the proposed schemes provide elegant means to remove noise from the EEG signal. Table 1 shows the computational complexity of various Block based normalized signed algorithms. Among all the algorithms the BBNLMS is more complex; it requires L+2 MACs and 1 division operations to implement the weight update equation. It is also clear from the table that the number of computation required for the proposed BBNSRLMS is independent of filter length (L). BBNSRLMS require only one MAC operation and one division.

Table 1 Computational Complexity Comparison of Block Based Normalized Signed algorithms

Algorithm	MAC's	ASC	Divisions
BBNLMS	L+2	Nil	1
BBNSRLMS	1	Nil	1
BBNSLMS	L	Nil	1
BBNSSLMS	Nil	L	1

3. Results and Discussions

To test the ability of the block based normalized algorithms and its variants discussed in this paper we performed various experiments on real EEG signals with a wide variety of wave morphologies. We used the benchmark Massachusetts Institute of Technology and Children's Hospital Boston (CHB-MIT) Scalp EEG records for our work (CHB-MIT database, 10). The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings. In our experiments we have considered a dataset of five EEG records: chb01, chb02, chb03, chb04 and chb05. We have used 600 samples of these signals for our experiments. For evaluating the performance of the proposed filter structures we have measured the signal-to-noise ratio improvement (SNRI) in decibels (dBs) using MATLAB program based on the following relation and compared with conventional LMS algorithm.

$$SNRI[db] = SNR_{output} - SNR_{input} = 10log\left(\frac{\sum_i |x_d(n) - x(n)|^2}{\sum_i |x_n(n) - x(n)|^2}\right)$$

Where x denotes the clean EEG, x_d is the denoised signal and x_n represents the noisy EEG signal. In this paper, we considered two dominant artefacts, namely Power Line Interference (PLI) and Electrocardiogram Artifact (ECG). To evaluate the performance signal to noise ratio improvement (SNRI) is measured.

Adaptive Power-line Interference Cancellation

The input to the filter is EEG signal corrupted with a PLI of amplitude 1mv, frequency 60Hz and sampled at 200Hz. The reference signal is synthesized sinusoidal noise generated in the noise generator; the output of the filter is recovered signal. The contaminated EEG signal is applied as input x(n) = $s_1 + n_1$, the correlated noise reference is applied as n_2 and the output is y(n). Various filter structures are implemented using overlapping block filters which are BBNLMS, BBNSRLMS, BBNSLMS and BBNSSLMS algorithms. The simulation results of chb01 for adaptive PLI removal using block based normalized algorithms and its signed versions are shown in Fig. 2.

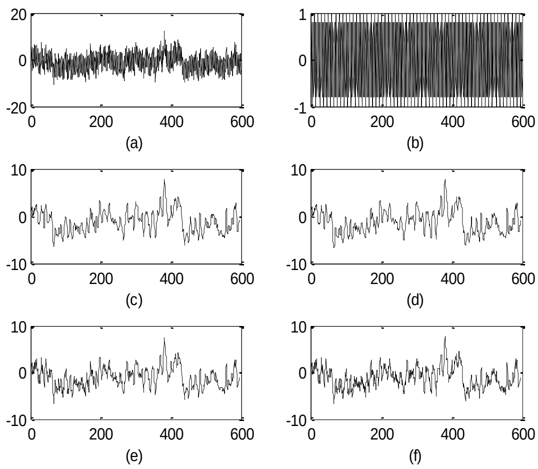

Fig 2: Typical filtering results for PLI cancellation using block based data normalized adaptive filtering techniques: (a) EEG signal(chb01) with PLI, (b) real PLI noise (c) recovered signal using BBNLMS algorithm, (d) recovered signal using BBNSRLMS algorithm, (e) recovered signal using BBNSLMS algorithm, (f) recovered signal using BBNSSLMS algorithm.

Table 2 SNR Contrast of Block based normalized adaptive filters for the removal of PLI

Rec.No	LMS	BBN LMS	BBNSR LMS	BBNS LMS	BBNSS LMS
Chb01	7.1584	15.4571	14.4796	13.1463	11.0382
Chb02	7.9482	16.0394	15.1493	14.5825	12.1837
Chb03	7.4816	15.2945	14.0935	13.3802	11.5824
Chb04	6.8396	15.3406	14.7936	13.0249	11.3946
Chb05	8.4957	16.2847	14.8325	14.3485	12.4915
Average	**7.5847**	**15.6832**	**14.6669**	**13.6964**	**11.7380**

For all the figures in this section number of samples is taken on x-axis and amplitude on y-axis, unless stated. Table 2 shows the SNR for the dataset. From SNR measurements it is found that BBNLMS algorithm outperforms conventional LMS algorithm with an average SNR of 15.6832 dB. And BBNSRLMS gives high SNR 14.6669 dB among all the sign variants of BBNLMS. . In the reduction of PLI artefacts BBNLMS performs better in terms of SNR, however BBNSRLMS with single multiplication achieves SNR slightly less than that of BBNLMS. So we consider BBNSRLMS as the best Adaptive noise canceller for PLI artefacts with reduced computational complexity.

Adaptive Cancellation of ECG Artefacts

The input to the filter is EEG signal contaminated with ECG noise; this is applied to a noise canceller shown in Figure 1. The reference signal is a real ECG noise. The contaminated EEG signal is applied as input x(n) = s1 + n1, the correlated noise reference is applied as n2 and the output is y(n). Various filter structures are implemented using overlapping block filters which are BBNLMS, BBNSRLMS, BBNSLMS and BBNSSLMS algorithms. The simulation results of chb01 for adaptive PLI removal using block based normalized algorithms and its signed versions are shown in Fig. 2.

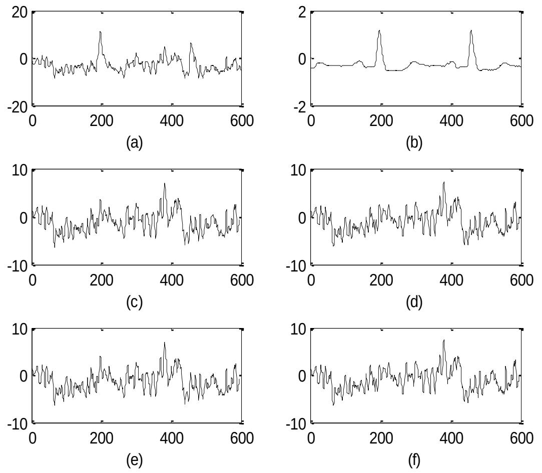

Fig 3: Typical filtering results for ECG artefact cancellation using block based data normalized adaptive filtering techniques: (a) EEG signal(chb01) with ECG noise, (b) real ECG noise (c) recovered signal using BBNLMS algorithm, (d) recovered signal using BBNSRLMS algorithm, (e) recovered signal using BBNSLMS algorithm, (f) recovered signal using BBNSSLMS algorithm

For all the figures in this section number of samples is taken on x-axis and amplitude on y-axis, unless stated. Table 2 shows the SNR for the dataset. From SNR measurements it is found that BBNLMS algorithm outperforms conventional LMS algorithm with an average SNR of 14.3915 dB. And BBNSRLMS gives high SNR 14.1194 dB among all the sign variants of BBNLMS. . In the reduction of ECG artefacts BBNLMS performs better in terms of SNR, however BBNSRLMS with single multiplication achieves SNR slightly less than that of BBNLMS. So we consider BBNSRLMS as the best Adaptive noise canceller for ECG artefacts with reduced computational complexity.

Table 3 SNR Contrast of Block based normalized adaptive filters for the removal of ECG artefact

Rec.No.	LMS	BB NLMS	BB NSRLMS	BB NSLMS	BB NSSLMS
Chb01	7.9145	14.0624	13.9401	12.8668	11.1904
Chb02	7.4193	14.4927	14.1493	12.9374	12.0492
Chb03	7.3274	14.4046	14.2857	13.2842	11.2835
Chb04	7.3947	14.3957	14.0283	13.4902	11.0934
Chb05	7.6193	14.6024	14.1936	13.5923	11.3928
Average	**7.5330**	**14.3915**	**14.1194**	**13.2341**	**11.4018**

Conclusion

In this paper the PLI and ECG artefacts removal from EEG signal using BBNLMS algorithm based adaptive filter is proposed and tested on real EEG signals obtained from CHB-MIT data base. Simulation results confirm that the BBNSRLMS filter reduces both PLI and ECG noise efficiently with high signal to noise ratio along with reduced number of computations when compared to conventional LMS based filter.

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